USING MACHINE LEARNING TECHNIQUES FOR DATA QUALITY MONITORING AT CMS EXPERIMENT

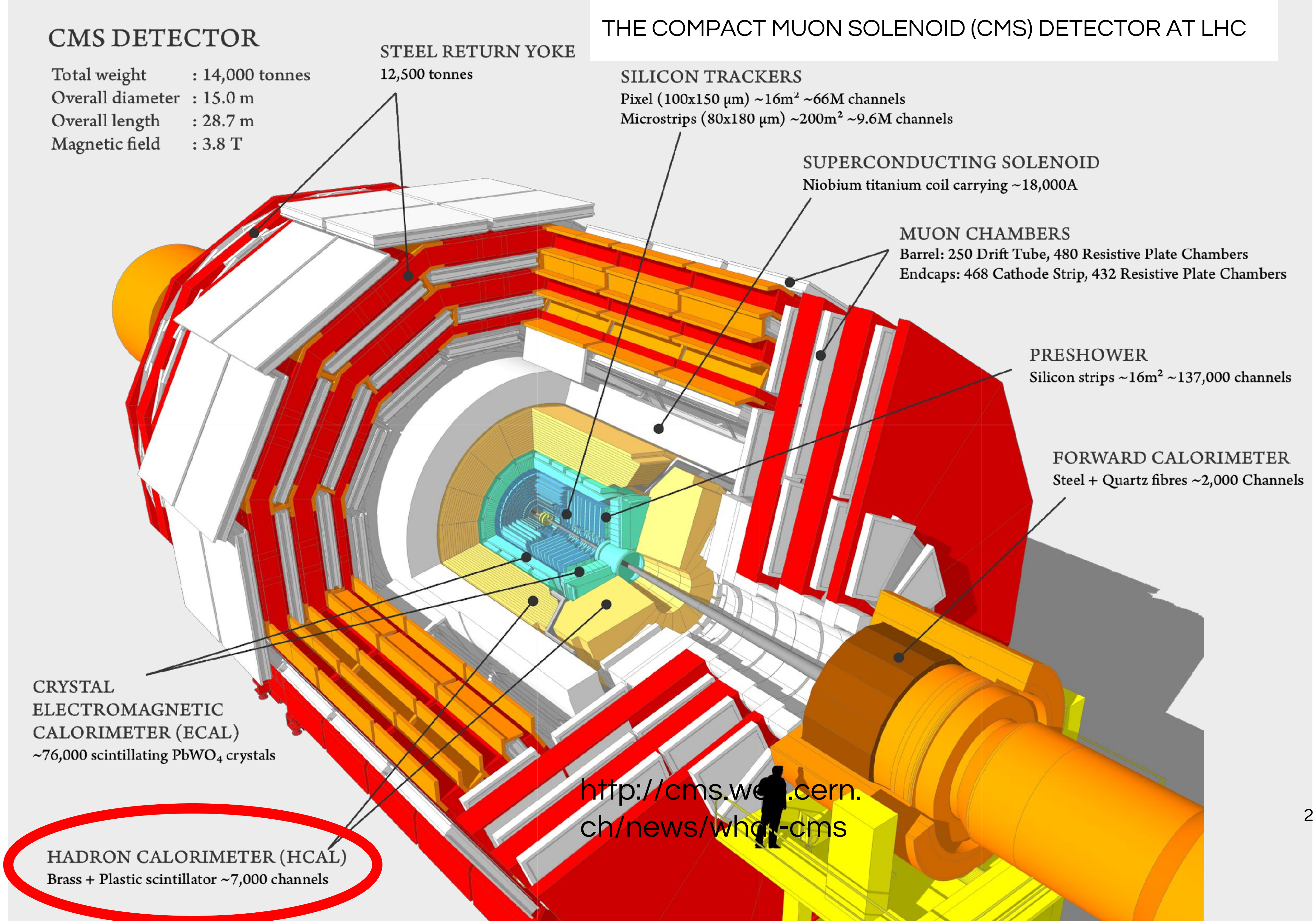
GUILLERMO A. FIDALGO RODRÍGUEZ

PHYSICS DEPARTMENT

UNIVERSITY OF PUERTO RICO MAYAGÜEZ

New Perspectives 2018 18-19 June 2018 Fermilab

THE COMPACT MUON SOLENOID (CMS) DETECTOR AT LHC



http://cms.we .cern. ch/news/wh -cms

OBJECTIVES

- Apply recent progress in Machine Learning techniques regarding automation of DQM scrutiny for HCAL
  - To focus on the Online DQM.
  - To compare the performance of different ML algorithms.
  - To compare fully supervised vs semi-supervised approach.
- Impact the current workflow, make it more efficient and can guarantee that the data is useful for physics analysis.

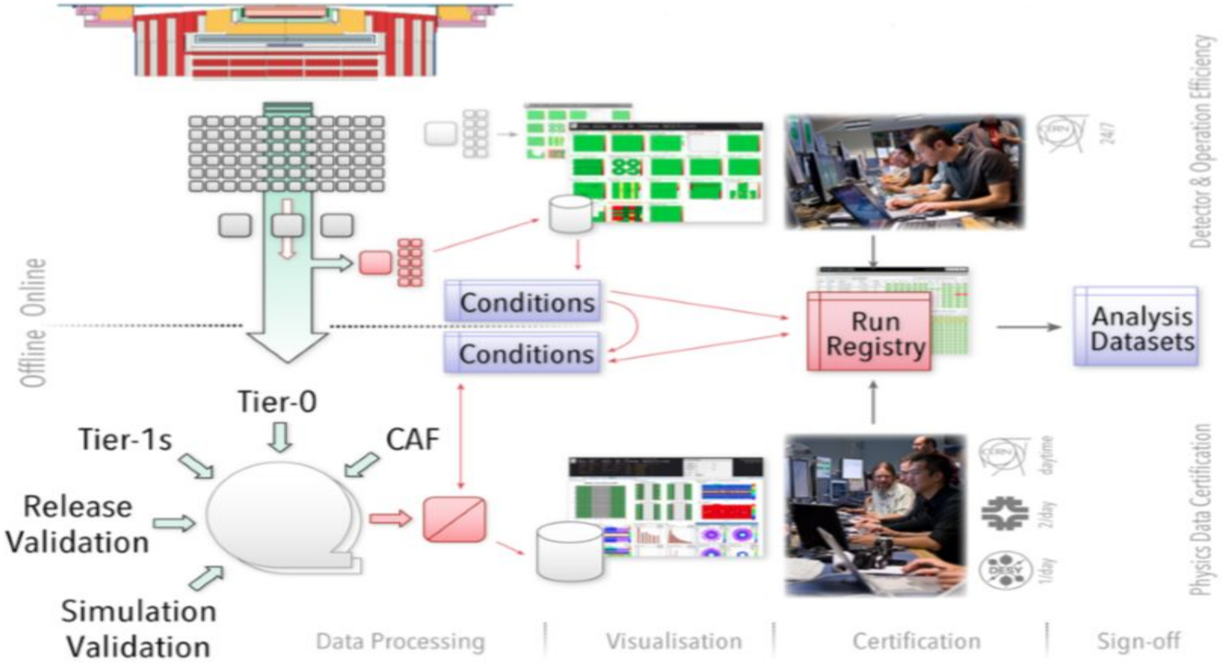
CHALLENGE

- Make sure detector behaves well to perform sensible data analysis.
- Reduce man power to discriminate good and bad data, spot problems, save time examining hundreds of histograms.
    - By building intelligence to analyze data, raise alarms, quick feedback.

- Implementing the best architecture for neural networks
    - Underfitting - Too simple and not able to learn
    - Overfitting - Too complex and learns very specific and/or unnecessary features
- There is no rule of thumb
    - Many, many, many…… possible combinations.

WHAT IS DATA QUALITY MONITORING (DQM)?

- Two kinds of workflows:
- Online DQM
  - Provides feedback of live data taking.
  - Alarms if something goes wrong.
- Offline DQM
  - After data taking
  - Responsible for bookkeeping and certifying the final data with fine time granularity.



HYPOTHESIS AND PROJECT QUERIES

Queries

- Can we make an algorithm that identifies anomalies in the data flow?

Hypothesis

- We can develop a ML algorithm that takes the images as data and determine whether or not an error is occurring.

Rationale

- Since this algorithm takes images as inputs it can learn to compare the images given with a baseline and correctly identify patterns and deviations from the baseline.

TOOLS AND DATA PROCESSING

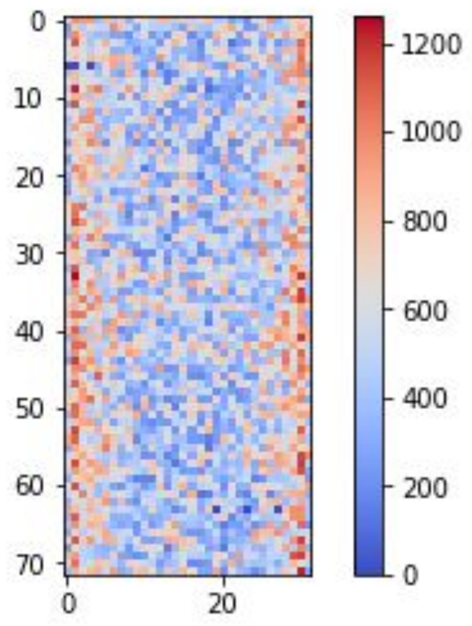
- Working env: python Jupyter notebook
- Keras (with Tensorflow as backend) and Scikit-learn
  - Creation of a model
  - Train and test its performance
- The input data consists of occupancy maps
  - one map for each luminosity section
  - Used 2017 good data and generate bad data artificially

IMAGE ANALYSIS TERMINOLOGY

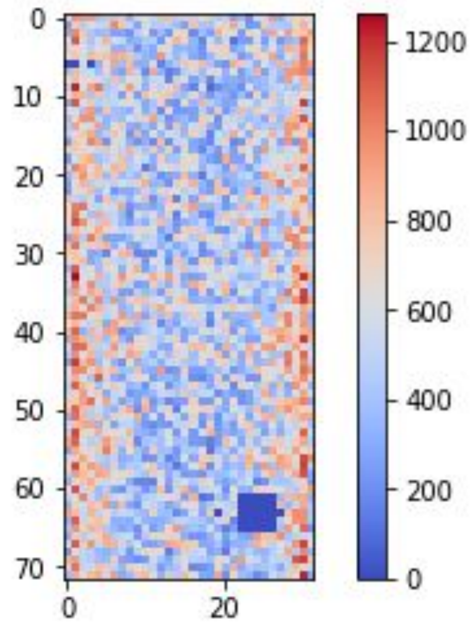
- Hot - image with noisy (red) channels
- Dead - image with inactive (blue) channels
- Good - regular images that are certified for analysis
- Model - an ML algorithm's structure
- Loss - number that represents distance from target value

IMAGES AND READOUT CHANNELS USED AS INPUTS FOR THE ML ALGORITHM

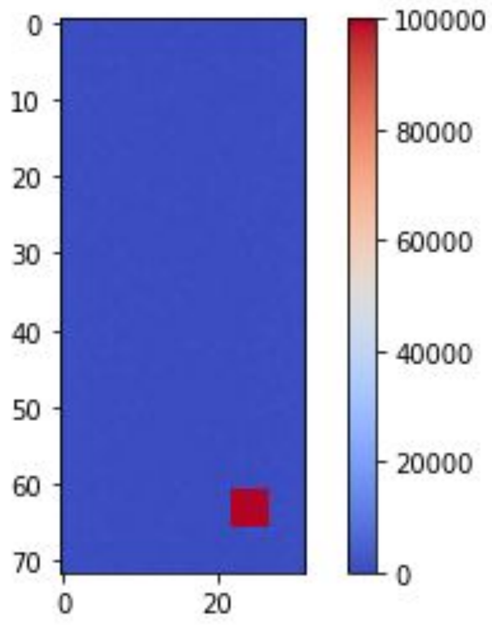
- Supervised and Semi-Supervised Learning
- 5x5 problematic region with random location
- 5x5 (readout channels) problematic region with fixed location



Good

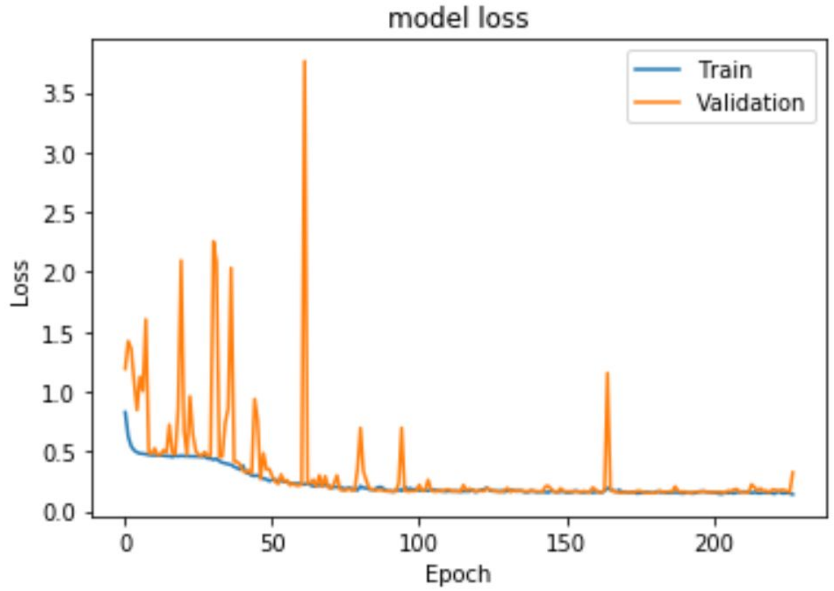


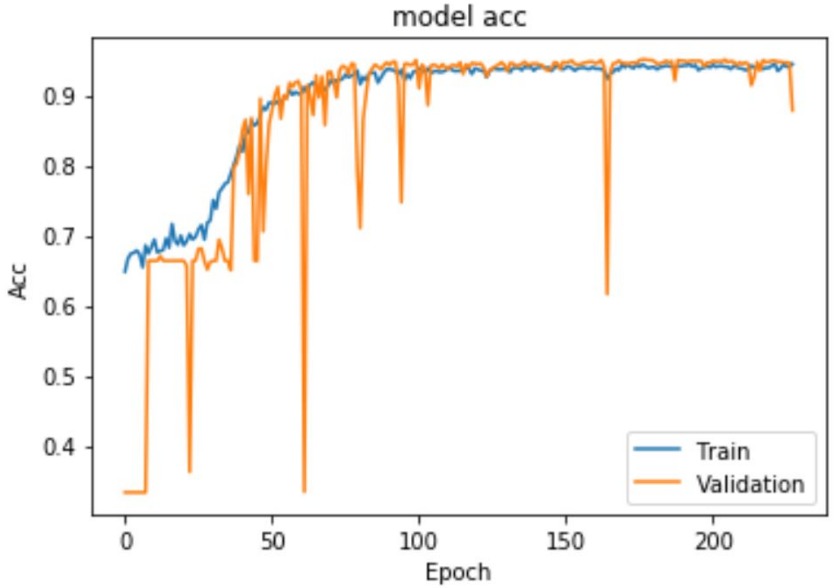
Dead



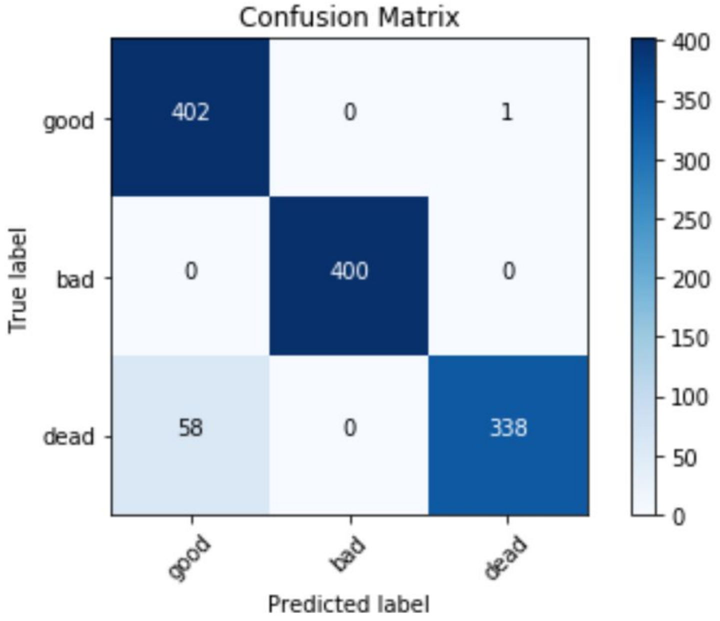
Hot

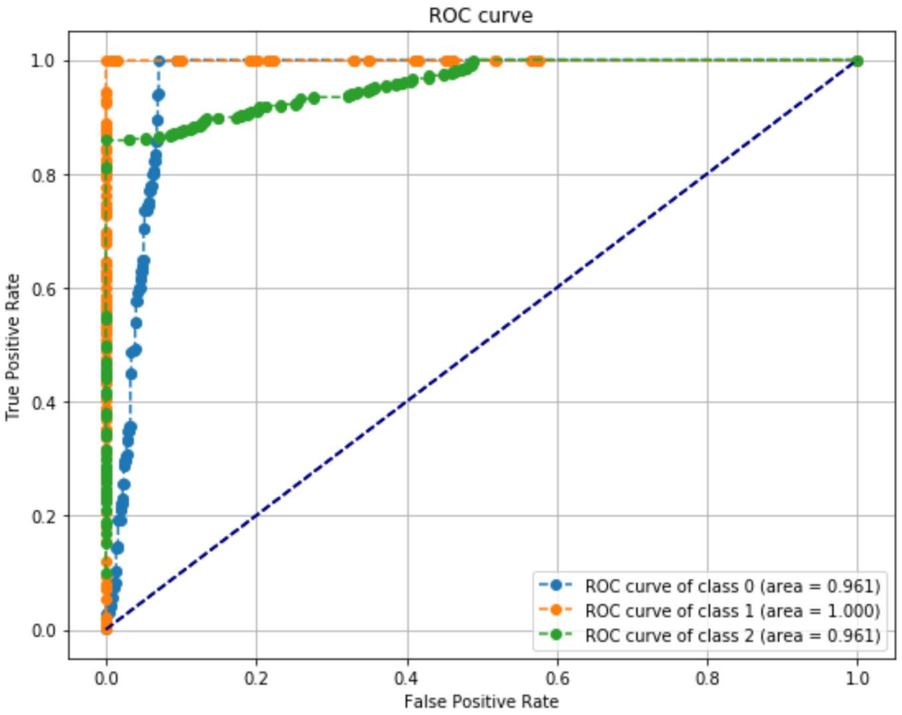
SUPERVISED LEARNING



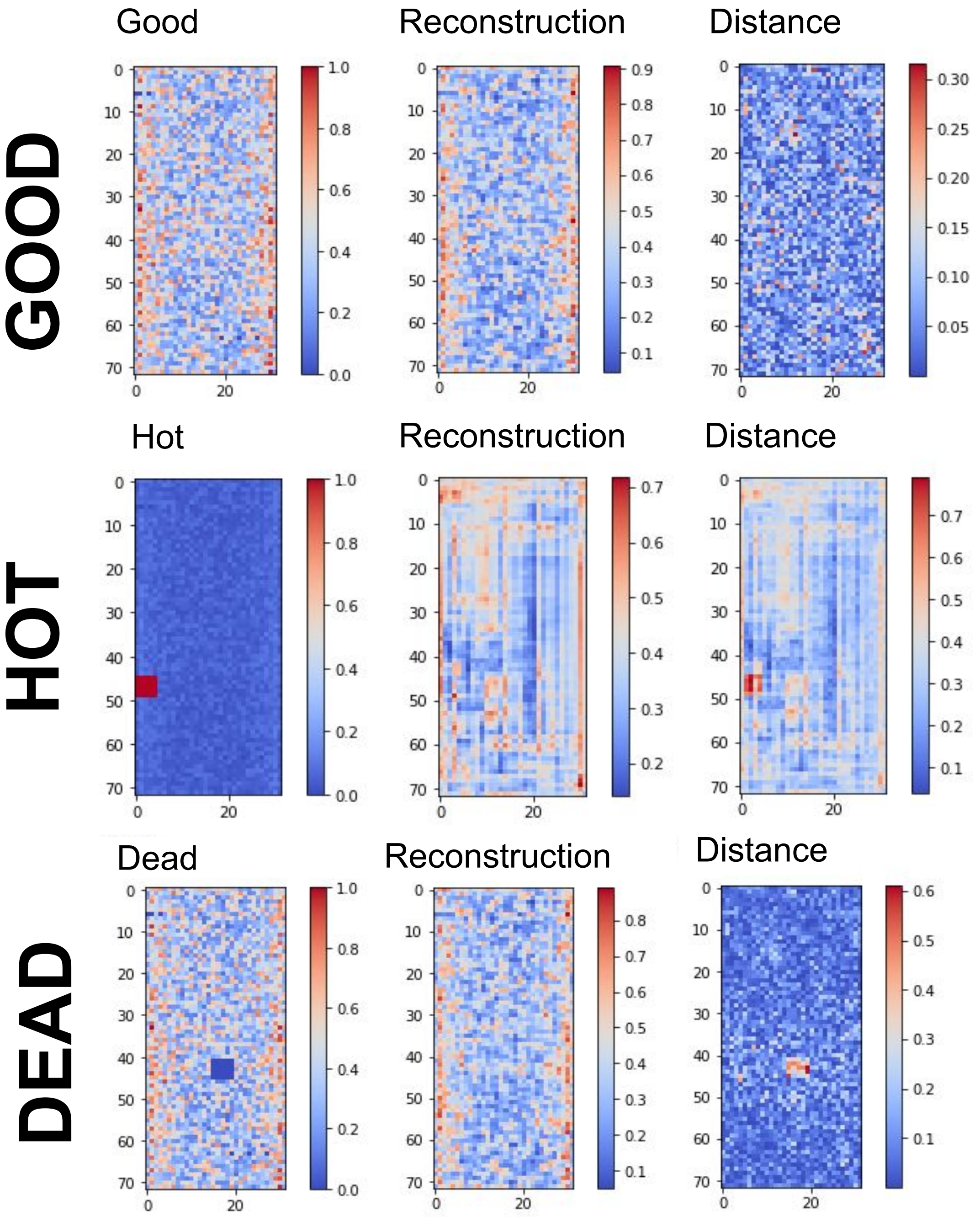


accuracy score: 0.950792326939



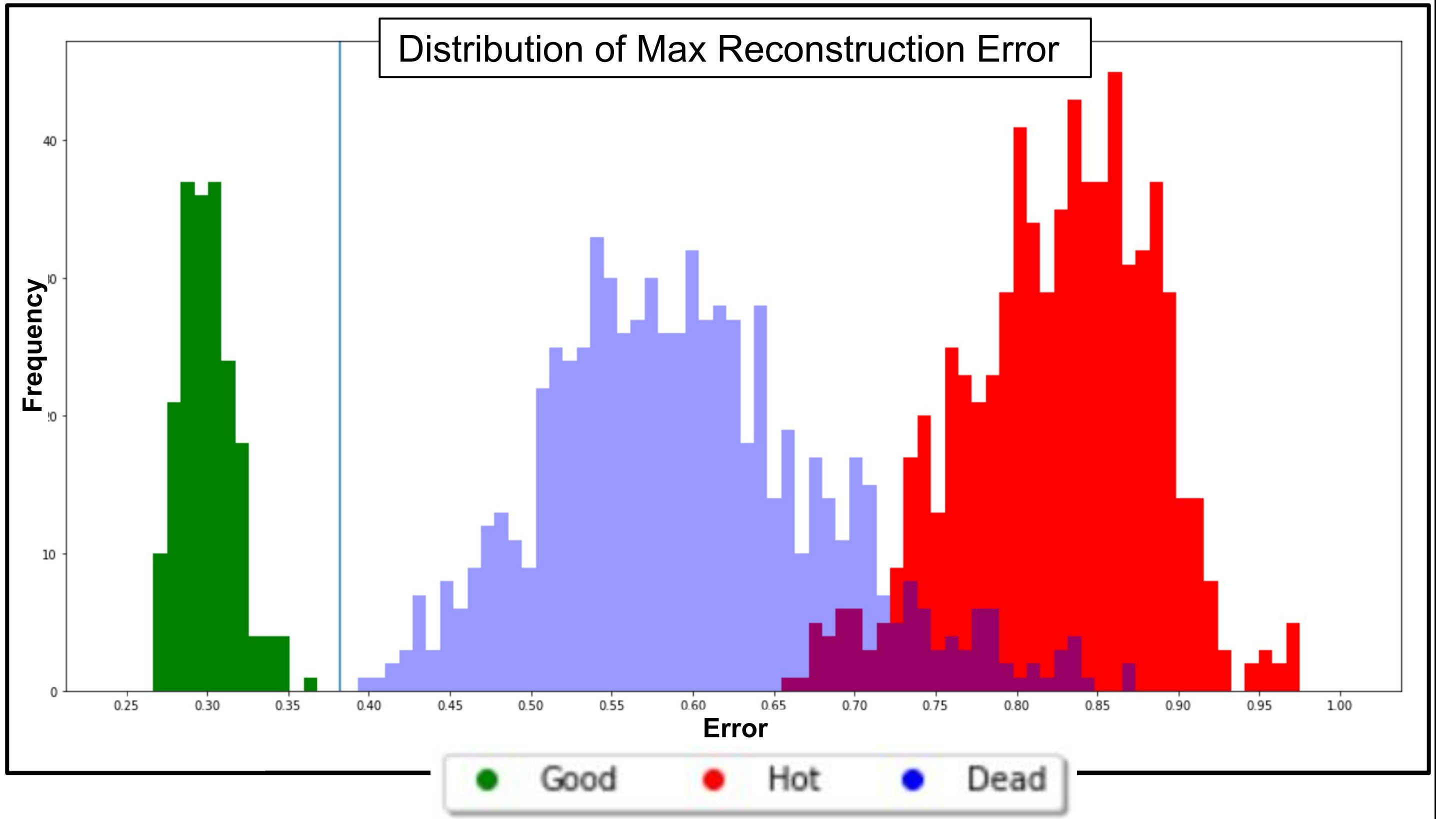


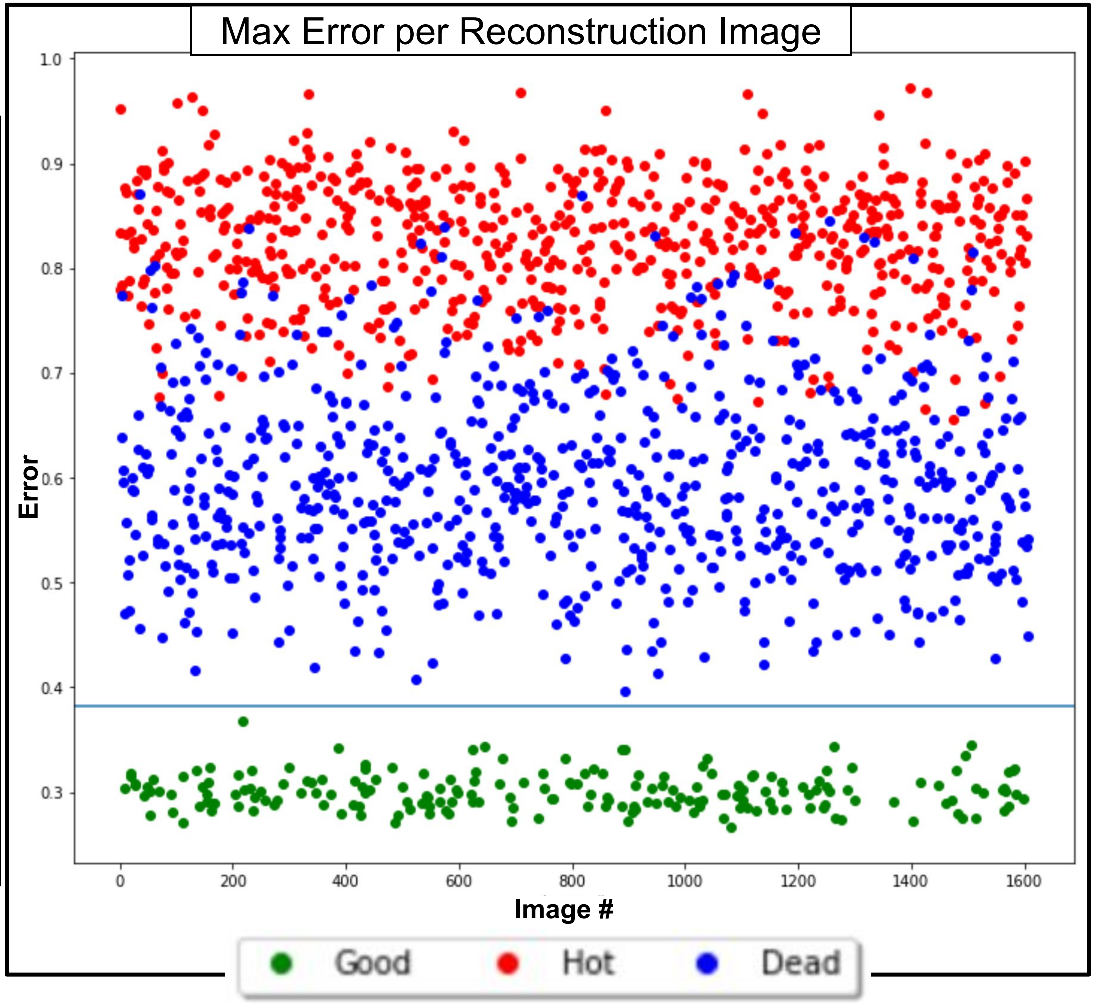
SEMI SUPERVISED LEARNING



- Trained only on good images
- Expected to see better reconstruction for good images and a much different reconstruction for bad images.
- Bad images have 5x5 bad regions
  - Hot
  - Dead
- Images have been normalized
- this architecture seems to perform best for us.

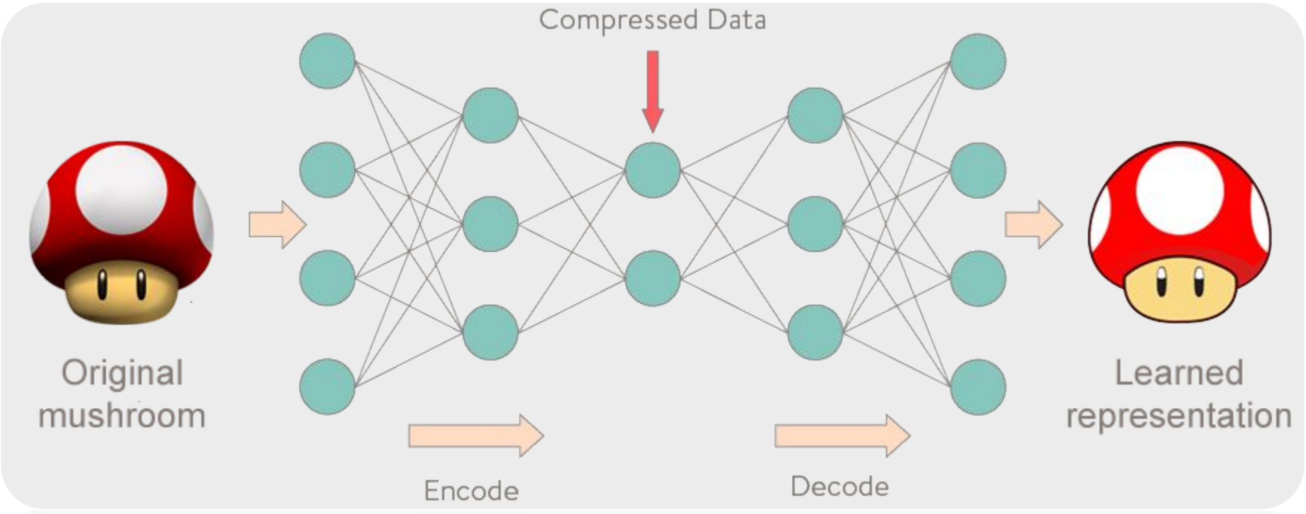
ERROR DISTRIBUTION PER IMAGE CLASS

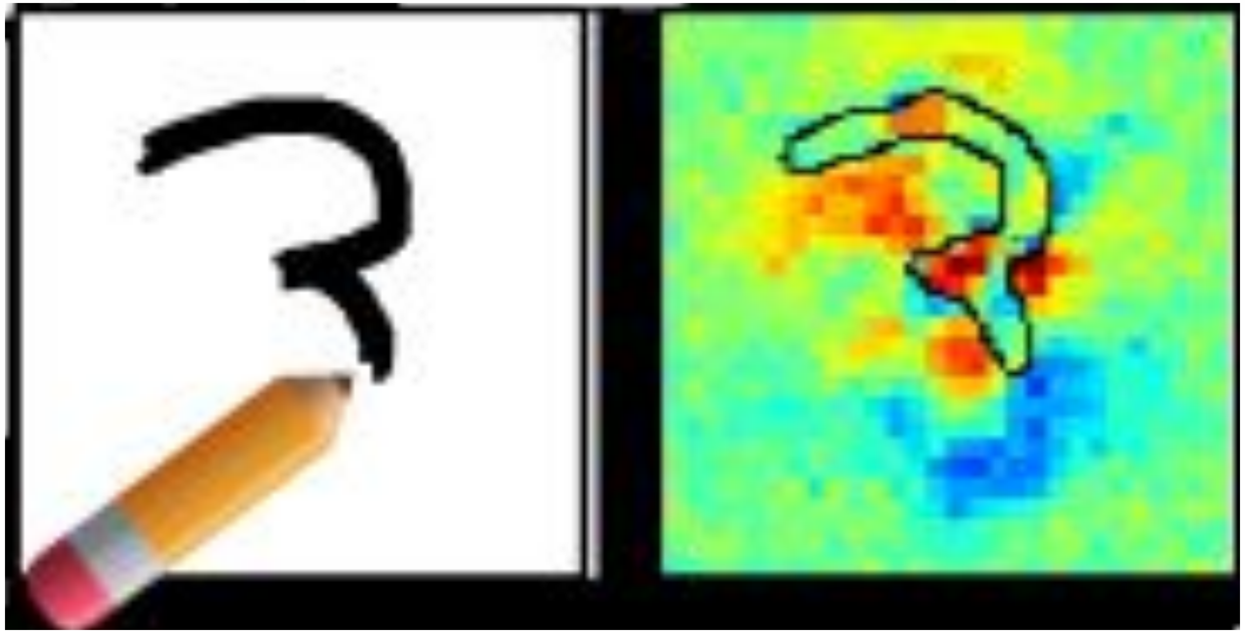




WHAT'S NEXT?

- Why and exactly what is it learning?
- Can we make it work with something more realistic?
  - 1x1 bad region (channel)
  - Can it identify what values should be expected after each lumi-section?
  - Move from artificial bad data to real cases of bad data (in progress)





Acknowledgments

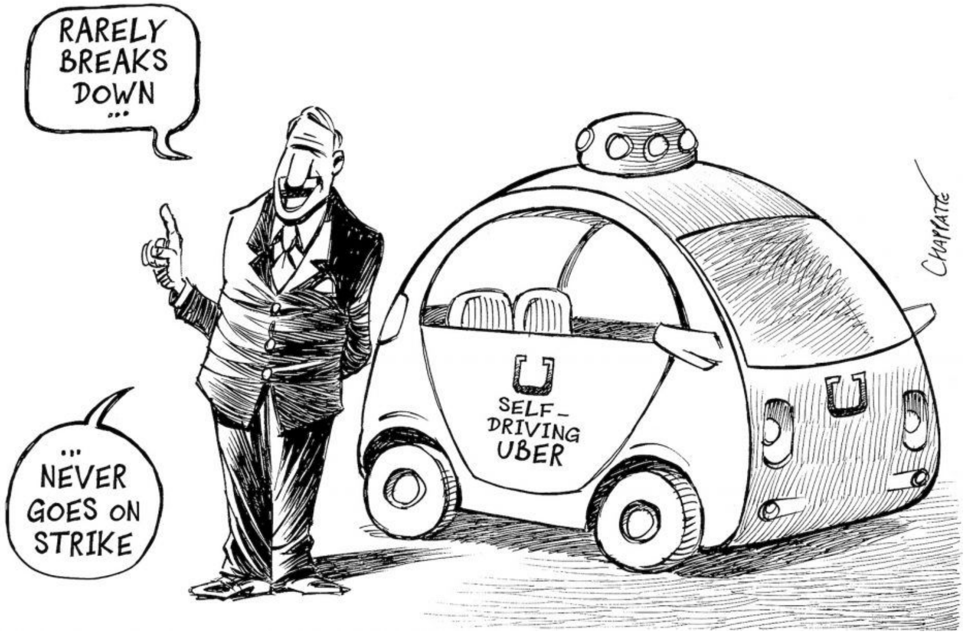
- The US State Dept.
- The University of Michigan
- CERN/CMS
- Federico De Guio , Ph.D (Texas Tech)
- Nural Akchurin, Ph.D (Texas Tech)
- Sudhir Malik , Ph.D (University of Puerto Rico Mayagüez)
- Steven Goldfarb, Ph.D (University of Melbourne)
- Jean Krisch, Ph.D (University of Michigan)

Thank You!

BACKUP

HOW TO AUTOMATE THE DATA QUALITY CHECKS? USE MACHINE LEARNING!

- It's everywhere now!
  - A.I. Learning
  - Self-driving cars
  - How do Google/Facebook know what you want?
  - Face/Handwriting Recognition
- In our case everything is reduced to a classification problem
  - Anomaly Detection



Machine Learning libraries

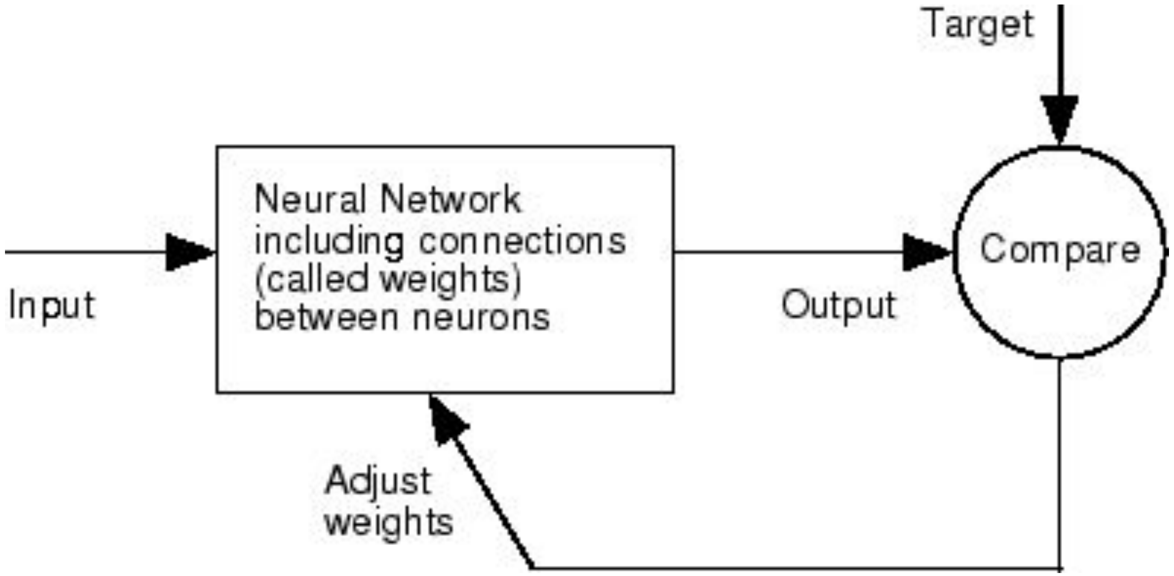
SCIKIT-LEARN

- Pre-defined models
  - Logistic Regression
  - MLP
- Not much control over the model’s architecture
- Very useful for testing performance

KERAS

- Make your own models
  - A bit sophisticated
  - Only for making NN
- Neural Networks
  - Deep Convolutional
    - Best with image recognition

How to train a model



Gradient Descent

The "Learning" in Machine Learning.

Update the values of X (punish) it when it is wrong.

$$\boxed{X = X - \eta\nabla(X)}$$

X: weights or biases

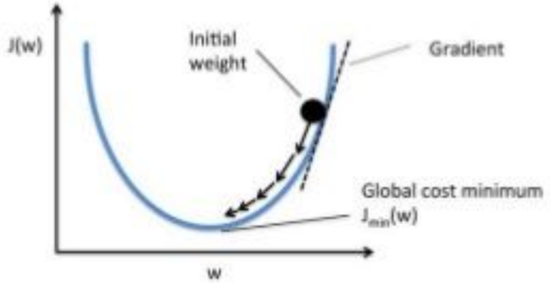
η: Learning Rate (typically 0.01 to 0.001)

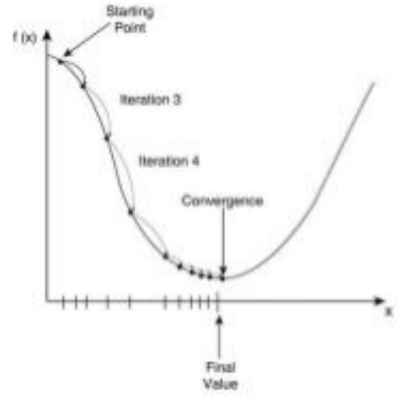
η :The rate at which our network learns. This can change over time with methods such as Adam, Adagrad etc. (hyperparameter)

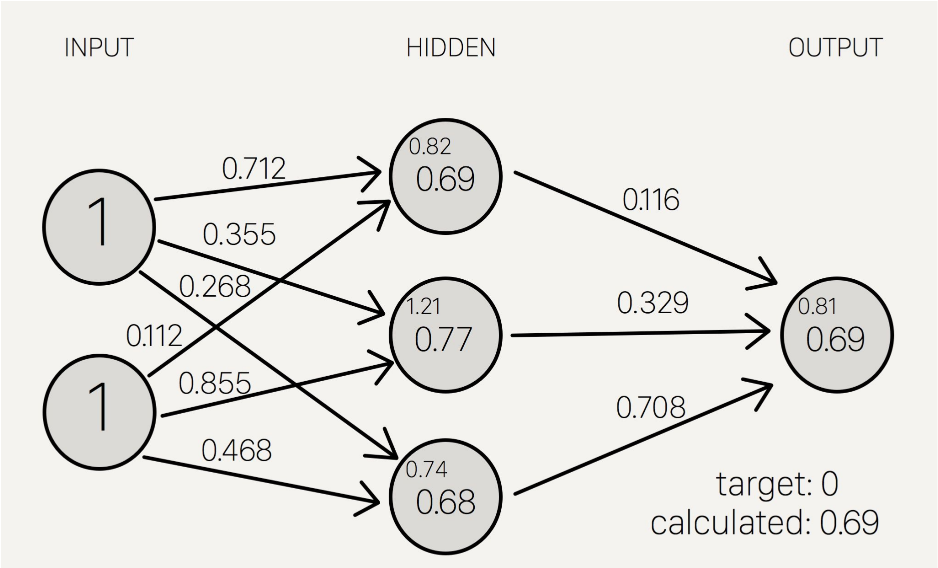
∇(x): Gradient of X

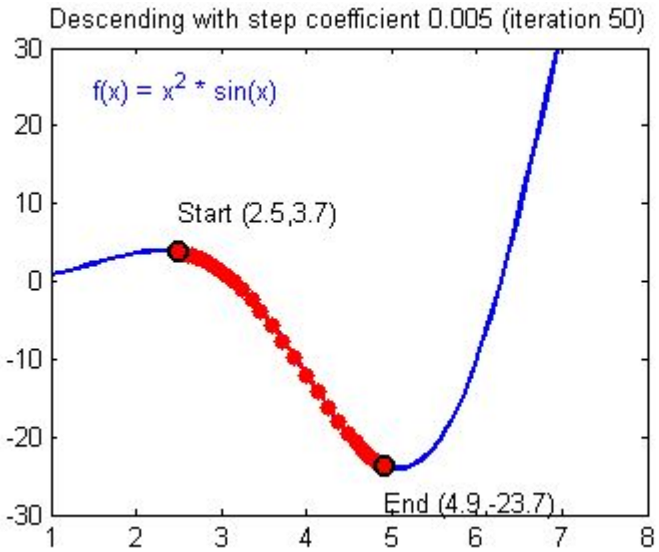
We seek to update the weights and biases by a value indicating how "off" they were from their target.

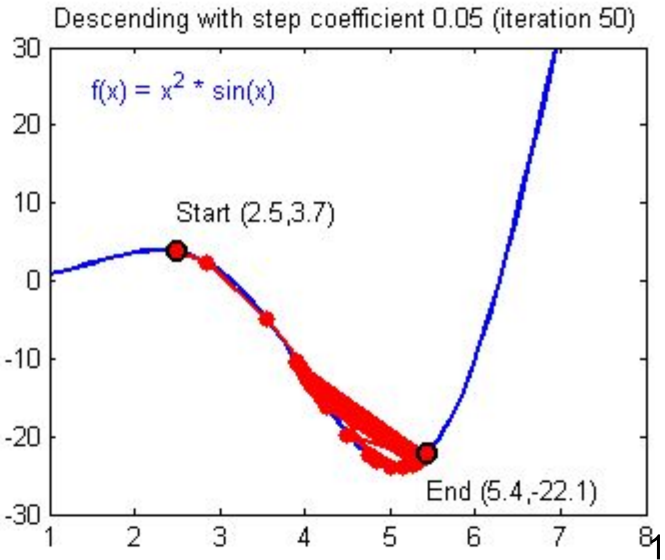
Gradients naturally have increasing slope, so we put a negative in front of it to go downwards



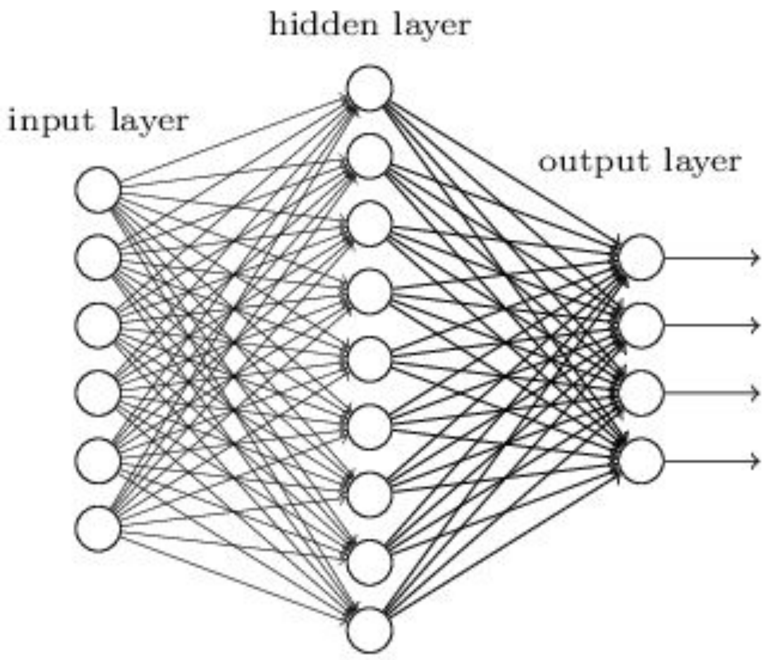




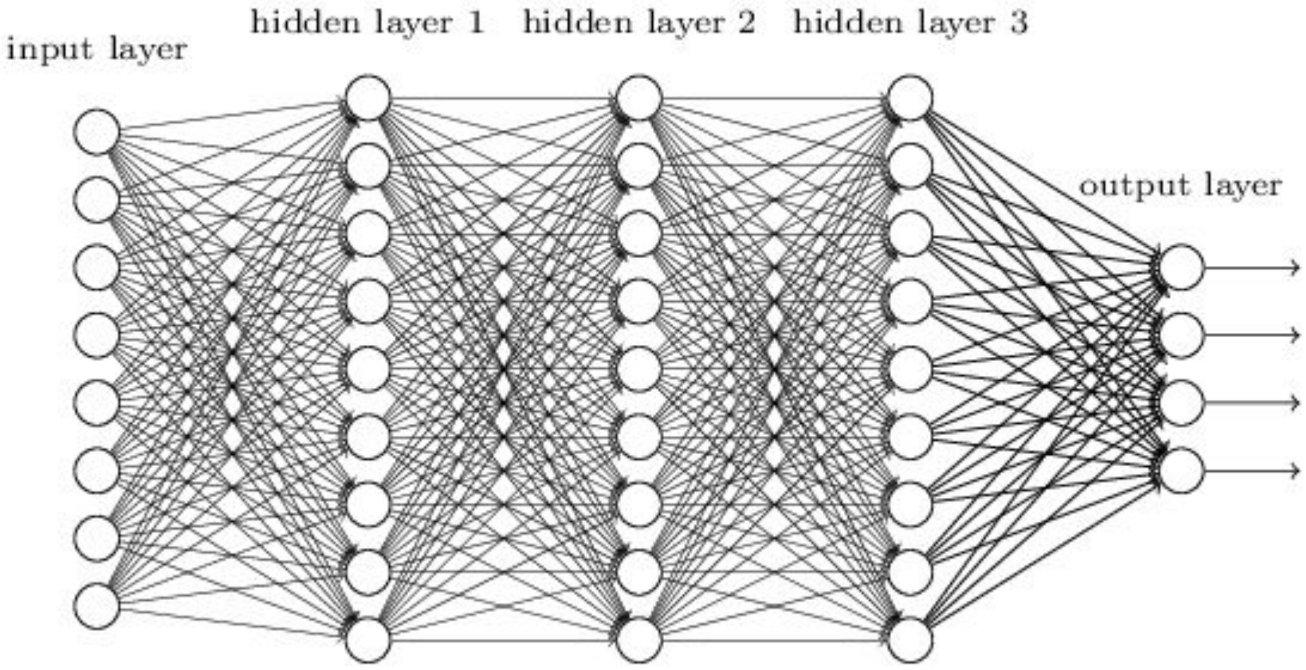




"Non-deep" feedforward neural network



Deep neural network



HOW A DEEP NEURAL NETWORK SEES

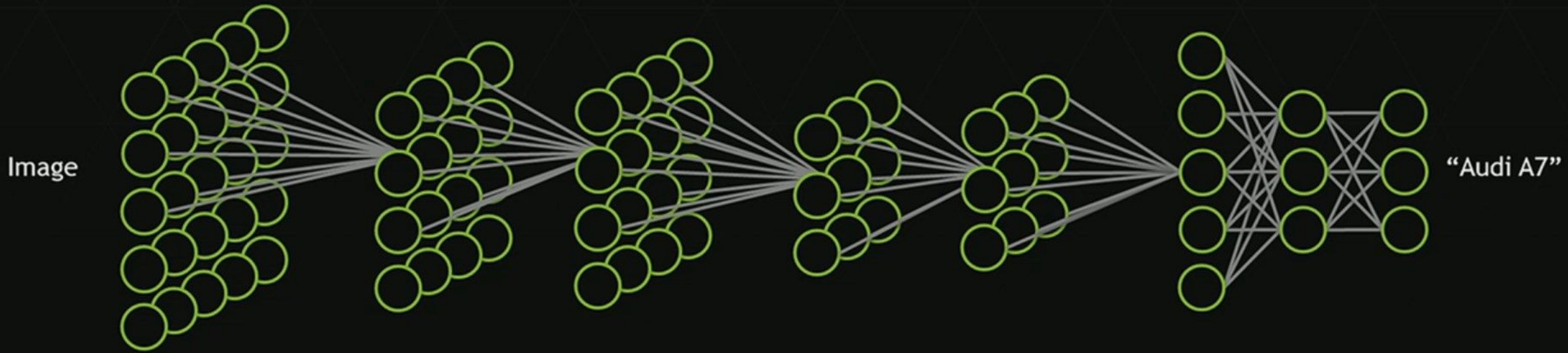
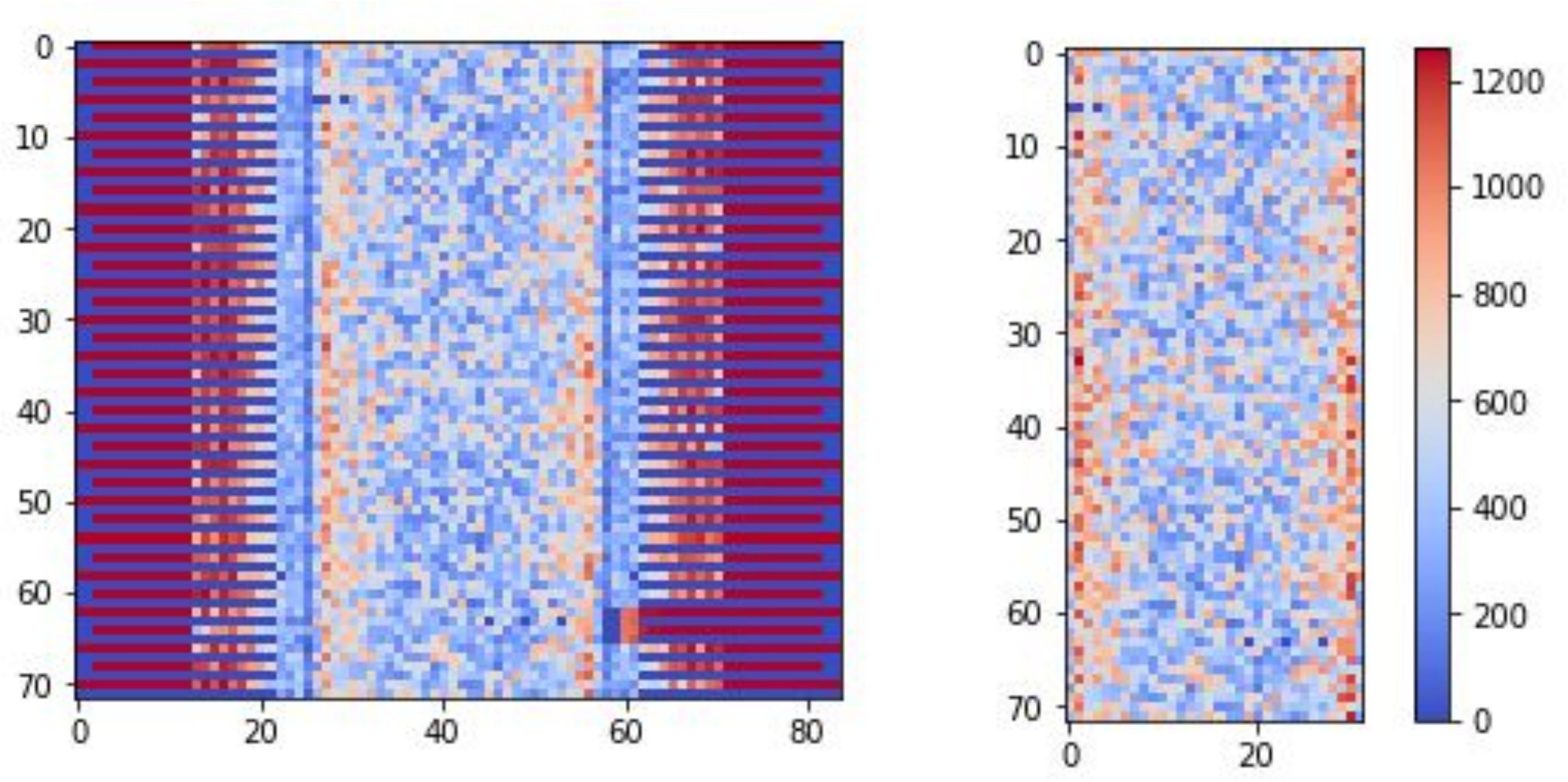


Image source: "Unsupervised Learning of Hierarchical Representations with Convolutional Deep Belief Networks" ICML 2009 & Comm. ACM 2011
Honglak Lee, Roger Grosse, Rajesh Ranganath, and Andrew Ng.

SAMPLE IMAGES TO STUDY

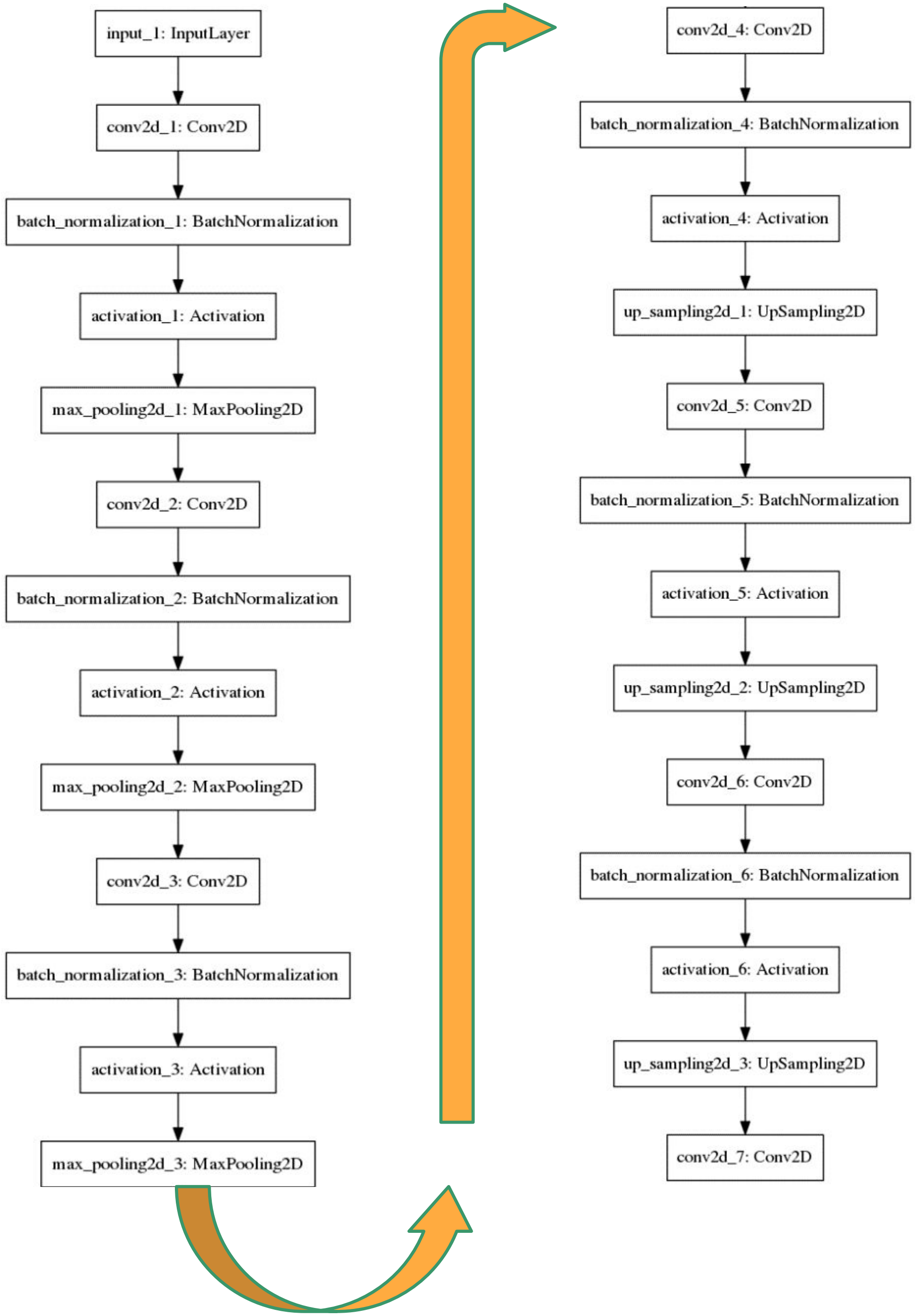


NEW ARCH.

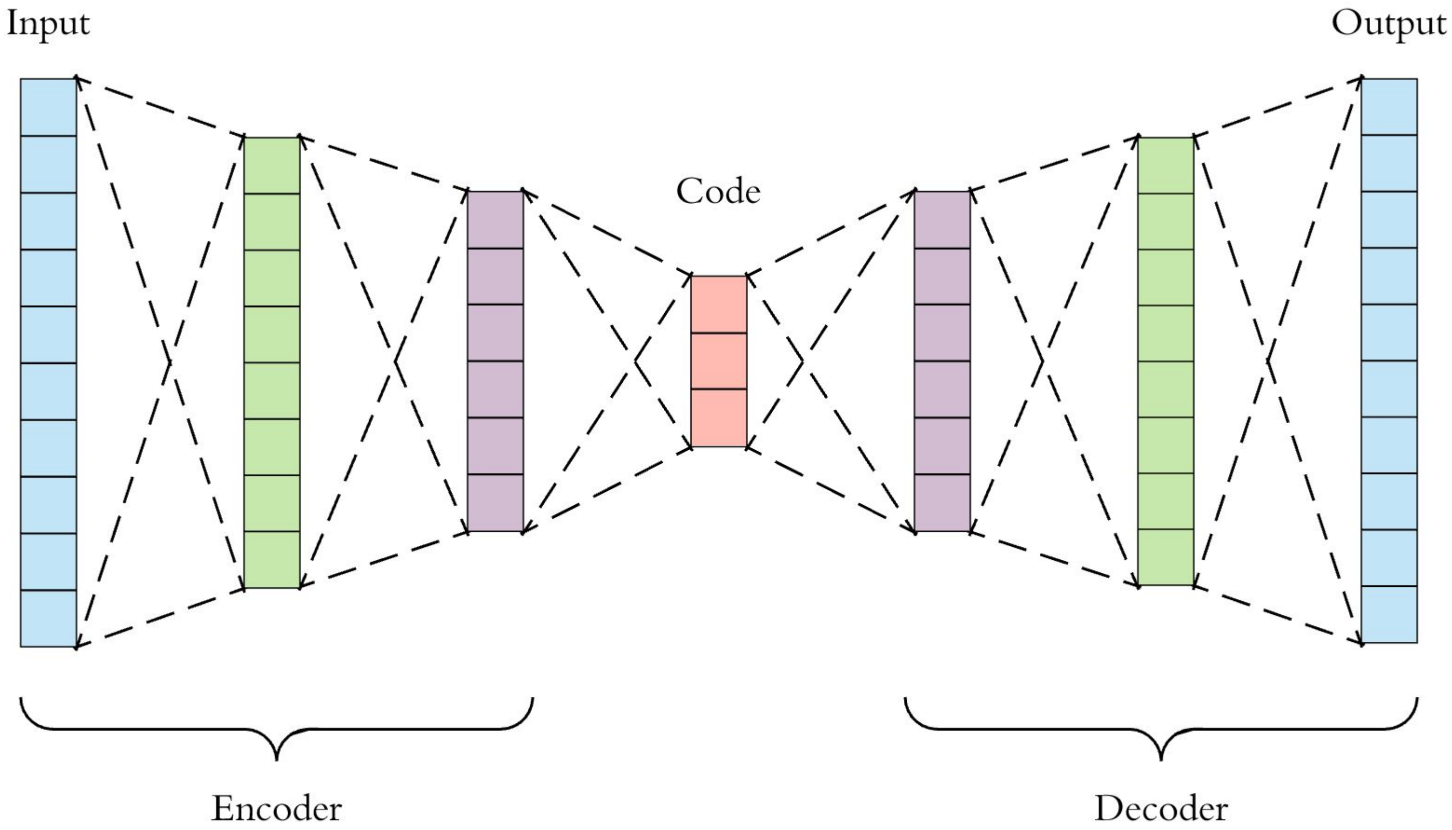
```
model = Sequential()

model.add(Conv2D(10, kernel_size=(2, 2), strides=(1, 1),input_shape=input_shape))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(8, kernel_size=(3, 3),strides=(1, 1)))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(8,kernel_size=(1,1)))
model.add(BatchNormalization())
model.add(Activation('relu'))

model.add(Dropout(0.25))
model.add(Flatten())

model.add(Dense(8))
model.add(BatchNormalization())
model.add(Activation('relu'))

model.add(Dense(3, activation='softmax'))


model.compile(loss='categorical_crossentropy',
              optimizer='adam',#Adam(lr=1e-3),
              metrics=['accuracy'])
```

ARCHITECTURE

```
input_img = Input(shape=(input_shape))  # adapt this if using `channels_first

x = Conv2D(86, (3, 3), padding='same')(input_img)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(64, (3, 3), padding='same')(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = MaxPooling2D((2, 2), padding='same')(x)
x = Conv2D(32, (3, 3), padding='same')(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
encoded = MaxPooling2D((2, 2), padding='same')(x)

# at this point the representation is (4, 4, 8) i.e. 128-dimensional

x = Conv2D(32, (3, 3), padding='same')(encoded)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(64, (3, 3), padding='same')(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = UpSampling2D((2, 2))(x)
x = Conv2D(86, (3, 3), padding='same')(x)
x = BatchNormalization()(x)
x = Activation('relu')(x)
x = UpSampling2D((2, 2))(x)
decoded = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)

autoencoder = Model(input_img, decoded)
autoencoder.compile(optimizer='adadelta', loss='mse')
```



Auto-Encoder ARCHITECTURES



- The bottleneck structures work using dimensionality reduction.
    - We are interested in seeing the features that are learned at the bottleneck stage of the AE after a successful reconstruction.
- We can use the reconstruction loss as a discriminant

REMARKS

- Slight improvement in the performance overall
- This is still a toy model with very specific examples
- Has not been tested with actual data
- Shows potential but there is room for improvement

- With this project I’ve noticed
    - There are many parameters to consider (architecture, nodes, optimizers)
    - There is no rule that let’s you know where to start or how to develop the correct model
    - There is a lot of trial and error.
    - You have to spend more time building the model than tuning the parameters.
- There have been many other versions of the architectures shown.
    - All show similar patterns for results

USED MODELS

For the models in the supervised approach :

- Loss is categorical cross entropy

For the more complex models

- Optimizer is Adam or other adaptive optimizers with similar results